# Exploration of optimal time steps for daily precipitation bias correction: A case study using a single grid of RCM on the Exe River in Southwest England

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**Abstract**

Bias correction is a necessary post-processing procedure in order to use Regional Climate Model (RCM) simulated local climate variables as the input data for hydrological models due to systematic errors of RCMs. Most of present bias correction methods adjust statistical properties between observed and simulated data based on a predefined duration (e.g., a month or a season). However, there is a lack of analysis about the optimal period for bias correction. This study has attempted to address the question whether there is an optimal number for bias correction groups (i.e. optimal bias correction period). To explore this optimal number we used a catchment in southwest England with the regional climate model HadRM3 precipitation data. The proposed methodology uses only one grid of RCM in the Exe catchment, one emission scenario (A1B) and one-member (Q0) among 11-members of HadRM3. We tried 13 different bias correction periods from 3-day to 360-day (i.e., the whole one year) correction using the quantile mapping method. After the bias correction a low pass filter is used to remove the high frequencies (i.e., noise) followed by estimating Akaike's information criterion. For the case study catchment with the regional climate model HadRM3 precipitation, the results showed that about 8-day bias correction period is the best. We hope this preliminary study about the optimum number of bias correction period for daily RCM precipitation will stimulate more research activities to improve the methodology with different climatic conditions so that more experience and knowledge could be obtained. Future efforts on several unsolved problems have been suggested such as how strong the filter should be and the impact of the number of bias correction groups on river flow simulations.

Keywords: regional climate model, bias correction, quantile mapping, digital filter, AIC

## 1. Introduction

From the hydrological cycle and water resources perspective, the impacts of climate change are of increasing interest to water resources managers (Bates et al. 2008, Compagnucci et al. 2001). Numerous studies have been done to assess the impacts of climate change on water resources which are based on climate variables from Global Climate Models (GCMs) and water resources models (Fung et al. 2011). However, because of the relatively low spatial resolution (100-250km) of GCMs, Regional Climate Models (RCMs) are widely used for regional impact studies at catchment scale (25-50km) (Qin et al. 2007, Fowler et al. 2007). Although RCMs are able to simulate local climate at a finer grid, it is well known that outputs from RCMs cannot be used as direct input data for hydrological models due to systematic errors (i.e., biases) and need post processing of the model outputs to remove biases (Sharma et al. 2007, Hansen et al. 2006, Christensen et al. 2008). Research has shown that typical systematic model errors of RCMs are shown as misestimation (over or under) of climate variables, incorrect seasonal variations of precipitation (Terink et al. 2009, Christensen et al. 2008, Teutschbein and Seibert 2010) and simulation of too many wet days of low intensity rainfall (drizzle effect) than the observed (Ines and Hansen 2006). Several studies on bias correction methodology have been done recently from simple linear scaling to complex quantile mapping methods (Piani et al. 2010, Johnson and Sharma 2011, Chen et al. 2011b, Chen et al. 2011a, Zhang et al. 2014b, Xu et al. 2014, Teutschbein and Seibert 2012).

Most of the existing bias correction methods are performed on monthly (i.e., 12 groups) or seasonal (i.e., 4 groups) bases, i.e., the monthly or seasonal statistic properties are equalised between the modelled and observed climate data (Bennett et al. 2011, Lafon et al. 2012, Lopez et al. 2009, Teutschbein and Seibert 2012). Lopez et al. (2009) applied a quantile mapping method based on the Gamma distribution for correcting RCM simulated daily precipitation in the southwest of England. The results showed that after bias correction the long term monthly mean precipitation of RCM became very similar to that of the observation data. Lafon et al. (2012) analysed the performance of four bias correction methods (linear, nonlinear, γ-based quantile mapping and empirical quantile mapping) for seven catchments spread across Great Britain. Scaling factors and distributions are based on monthly data for all the four bias correction methods. The results showed that all the methods showed some improvements in reducing the biases of RCM simulated precipitation. Teutschbein and Seibert (2012) compared the performance of four bias correction methods (linear scaling, local intensity scaling, power transformation and distribution mapping) and all the bias correction methods were on a monthly basis. The results showed that all those methods are capable of improving RCM outputs, especially the distribution mapping performed the best. Bennett et al. (2011) used Tasmania catchment in Australia to explore the performance of the quantile-quantile bias correction method and calculated correction factors for each season and for each percentile. After correction the spatial correlation between the observed and modelled seasonal and annual rainfall have been improved.

However, all of these studies did not provide the explanation on why monthly or seasonal period precipitation data have been used for bias correction. From the intuition, the number of bias correction groups controls the accuracy of the model: using fewer groups might smooth out the information contained within the observed and modelled data, while using too many groups might result in overfitting of the RCM precipitation to the observed precipitation. If the bias correction period is too long it may lose temporal information (in other words, variation within the bias correction period will be lost). On the other hand if the period is too short even the noise of natural variation will be matched. Hence, it is possible that there could be an optimal bias correction period. So far there are no reported studies on this topic. This study intends to explore the optimal bias correction period (i.e., optimal number of bias correction groups) which is based on a balance between the bias and the variance (the well-known trade-off between the bias and variance in mathematical modelling). A short bias correction period has more variance but less bias, while a long bias correction period has less variance but high bias. The Akaike's information criterion which is a measure of the goodness of fit of an estimated statistical model and leave-one-out cross validation are used to find the optimal number of bias correction groups. Before evaluating different number of groups, a low pass filter is applied to eliminate high frequencies and consider more meaningful underlying temporal change. A similar application has been done in assessing GCMs performance by using wavelets to evaluate the skill of GCMs in reproducing the observed low frequency variability (Johnson et al. 2011). Here, we do not propose a new bias correction method or evaluate the performance of different bias correction methods but explore the best window size for bias correction by applying a commonly used quantile mapping bias correction method. We would like to note that the proposed methodology uses only one grid of the Exe catchment which is located in the southwest of England, one emission scenario (A1B) and one-member (Q0) among 11-members of HadRM3 RCM precipitation because the purpose of this study is mainly to illustrate the logic of finding the optimal window size for bias correction of daily precipitation.

Although bias correction is a controversial issue (Muerth et al. 2013, Ehret et al. 2012) it is widely used in climate impact studies because practitioners can use the bias corrected data directly. Despite its wide usage, there are still many unsolved problems. For example, which bias correction method to apply is a controversial subject as well. On the one hand, some studies argue there is a  flaw with the quantile mapping (Madadgar et al. 2014) and claim that the conditional bias correction methodologies produce better results than the quantile mapping which is an unconditional approach. (Brown and Seo 2013, Verkade et al. 2013, Madadgar et al. 2014). On the other hand, the quantile mapping has been used for many practical datasets widely used by practitioners such as the well-known 'Future Flows Climate'

(Prudhomme et al. 2012) dataset which is an 11-member ensemble climate projection for Great Britain at a 1-km resolution. In this study we are not arguing that the quantile mapping is the only and the best method. Instead, it is a method used to illustrate the optimal window size methodology. For any other bias correction methods the same principle proposed here could be applied and the optimal window size could be studied.

## 2. Study Catchment and data

### 2.1 Study area

The Exe catchment is located in Southwest England. The catchment area is 1530 $km^2$ and its average annual rainfall is 1088 mm. The four major tributaries of River Exe are River Culm, River Barle, River Clyst and River Creedy, and the trunk flows into the sea via the Exe Estuary on the south coast of England. The main urban areas in the Exe catchment are Exeter, Crediton, Tiverton, Cullompton. Figure 1 shows the overview of the Exe catchment area. In this study the Thorverton catchment (606$km^2$) which is one of the Exe subcatchment is used. Daily time series of the observed precipitation data over the Thorverton catchment is derived from 5 rain gauges (extracted from the UK Met Office's MIDAS database) using the Thiessen polygon method for the baseline period (1961-1990).

### 2.2 Regional climate model (RCM) data

The climate data used in this research has been generated by HadRM3. HadRM3 is a Met Office Hadley Centre's regional climate model (resolution 25×25km) which is used to produce regional projections of the future climate from the global climate model HadCM3 (Murphy et al. 2009). In this study we used HadRM3 data driven by HadCM3 rather than using reanalysis data as the boundary conditions for HadRM3. The RCM data consist of one unperturbed member and 10 perturbed members driven by historical emissions and future emission scenario A1B which assumes a balance between fossil fuels and other energy sources. 31 parameters were selected for this perturbation from the unperturbed member representing cloud, convection, radiation, atmospheric dynamics, boundary layer, land surface and sea-ice. The HadRM3 Perturbed Physics Experiment Dataset (HadRM3-PPE-UK) provides time series data from 1950 to 2100. Detailed information about the HadRM3-PPE data can be found at http://badc.nerc.ac.uk/browse//badc/hadrm3/data/hadrm3-ppe-uk. The RCM 25km grid boxes are rotated 0.22$^{o}$ as shown in Figure 1. Here, among 11-members only the unperturbed RCM daily precipitation series for the baseline period 1961~1990 is used in this study and the grid is selected covering the Thorverton catchment.

## 3. Methodology

### 3.1 Statistical bias correction methods

The Gamma distribution is commonly used for rainfall distribution since it can provide a variety of distribution shapes (Wilks 1990). In this study the two parameter Gamma distribution is applied and its function is as follows:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta};\ x \geq 0;\ \alpha, \beta > 0 \qquad (1)$$

where, $\Gamma$ is gamma function, α is shape parameter, and β is scale parameter. Among various bias correction methods the quantile mapping method based on the Gamma distribution is selected for bias correction of the daily RCM simulated precipitation data. The objective is to map the observed and simulated quantiles using their corresponding Gamma distributions. The calendar year is divided into different segments and bias correction is performed within each segment individually. In this study, bias correction is conducted for various time periods independently after matching wet day frequency between the observed and RCM simulated precipitation data by modifying the RCM simulated data using a cut-off threshold (a commonly adopted approach). Daily Gamma cumulative distribution functions (CDFs) are built from each time period for both the observed and RCM simulated precipitation from 1961 to 1990. Figure 2 presents the schematic of the distribution mapping method. First, the value of the RCM simulated daily precipitation is found in the Gamma CDF and the corresponding cumulative probability from the observed Gamma CDF. Then the value of precipitation with the same cumulative probability is searched in the observed Gamma CDF. This value is the corrected value of the RCM simulated precipitation. The mapping equation can be expressed as follows:

$$X_{cor} = F^{-1}\left[F(X_{mod}\,;\,\alpha_{mod}\,\beta_{mod})\,;\,\alpha_{obs}\,\beta_{obs}\right] \qquad (2)$$

where, $F$ is Gamma CDF, $F^{-1}$ is its inverse function, $X_{cor}$ is the bias corrected data in the baseline period, α and β are shape and scale parameters of the Gamma distribution respectively. The subscripts *mod* and *obs* indicate the parameters from the RCM simulated precipitation and observed precipitation.

Usually the RCM simulated precipitation values have a numerous number of days with low precipitation compared with the observed precipitation. Therefore, a cut-off threshold is commonly used to remove low precipitation values in the model output in order to equalise the frequency of wet days between the observed and simulated precipitation before applying the quantile mapping method. After bias correction, the RCM simulated Gamma CDF is shifted to the observed Gamma CDF. In this study, to find out the optimal number of bias correction groups, bias correction has been done by 13 different time periods as follows and Figure 3 shows the schematic of bias correction with different bias correction periods : 3 days (120 groups), 4 days (90 groups), 8 days (45 groups), 15 days (24 groups), 30 days (12 groups), 40 days (9 groups), 45 days (8 groups), 60 days (6 groups), 72 days (5 groups), 90 days (4 groups), 120 days (3 groups), 180 days (2 groups) and 360 days (1 group). For both the observed and RCM simulated precipitation, the CDFs of each group are built from daily precipitation from 1961 to 1990 as shown in Figure 3.

### 3.2 Akaike's information criterion

In this study, to find out the optimum numbers of bias correction groups, Akaike's information criterion (Burnham and Anderson 2001) which is a measure of the goodness of fit of an estimated statistical model is applied.

$$\mathrm{AIC} = -2 \times ln(\mathrm{likelihood}) + 2 \times k \tag{3}$$

where, *ln* is the natural logarithm and $k$ is the number of parameters included in the model. The penalty for the model complexity is done by adding $k$ in AIC. As a result the optimal model is selected that fits well but has a minimum number of parameters. In this study, the more bias correction groups we divide the more complex the model will become and $k$ will get larger. When AICs of different models are compared, the model having the lowest AIC is the optimal. In practice, AIC is usually estimated using the residual sums of squares (RSS) from regression.

$$\mathrm{AIC} = n \times ln(\mathrm{RSS}/n) + 2 \times k \tag{4}$$

where, $n$ is the number of data points and RSS is the residual sums of squares. If the ratio of $n/k$ is less than 40 the following equation should be used instead to derive more reliable results.

$$\mathrm{AIC} = -2 \times ln(\mathrm{likelihood}) + 2 \times k + (2 \times k \times (k+1)/(n-k-1) \tag{5}$$

We are not considering only the model complexity as a major criterion but the overall accuracy of the bias corrected data since the model complexity is combined with RSS. AIC is an indicator to balance the model complexity and the closeness of the model to the observations. Without penalising for the complexity of the model, over-fitting would be an issue since the more complex the model is, the smaller temporal error will be in the bias correction. In this study the k is a good indicator of the complexity of the bias correction function (i.e., the number of parameters) since a smaller window size would have more parameters and will produce more transfer functions. The other verification measures without considering the complexity will suffer from an over-fitting problem.

### 3.3 Low pass signal filtering using FFT

Since both the observation and RCM precipitation data have fluctuations (i.e., noisy), which makes it difficult to evaluate the optimal number of bias correction groups, it is necessary to eliminate these high frequencies in order to consider more meaningful underlying temporal change. Without using filter the natural variation may dominate the signal but if we remove the noise the impact of the noise on AIC value can be reduced and the optimal number of bias correction period could be found. In this case, small bias correction periods are not reliable because of the large variations in unfiltered daily rainfall time series. As the bias correction period is increased, the results become more stable.

Here, a low pass filter based on the Fourier Transform is applied to filter out the noise, i.e. high frequency signals from the precipitation data and make the time series smoother to help identifying rainfall features between the observation and RCM data. The Fourier Transform is used to map signals from the time domain to the frequency domain. The Fourier Transform *F(w)* and inverse Fourier Transform *f(t)* are defined as follows.

$$F(w) = \int_{-\infty}^{\infty} f(t) e^{-iwt} dt \tag{6}$$

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(w) e^{iwt} dw \tag{7}$$

After the Fourier transform of the data, a variety of filters are explored to smooth the data time series to reduce fluctuations. In this study, the Hamming-window filter is applied as follows.

$$w(n) = 0.54 - 0.46\cos(\frac{2\pi n}{N-1}), \qquad 0 \leq n \leq N\text{-}1 \tag{8}$$

where, N is the length of the filter window.

We chose the cut-off frequency to filter out the noise in the precipitation which is determined on the basis of spectral analysis of the observed river flow. Therefore, the dominant frequencies of the observed flow have been selected for the cut-off frequency of the precipitation. When applying filter not only the cut-off frequency is considered but different number of filter coefficients are applied. The filter with large number of filter coefficients cuts off sharp frequencies but has poor time resolution, while the filter with small number of filter coefficients has a good time resolution but its frequency cut off may not be sharp enough. Here, we chose three different numbers of filter coefficients ($m$) 15, 30 and 60. This method can be justified since our major purpose with the rainfall data is for water resource management, i.e., the volume of water and the low pass filter can be considered as a catchment as shown in Figure 4. High frequencies of rainfall data will be removed by catchment filter resulting in low frequencies of river flow.

### 3.4 Cross validation

To evaluate the performance of different bias correction groups the leave-one-out cross validation is applied. Figure 5 shows the scheme of this method. Each of the 30 simulated years is processed once independently from the remaining 29 years used for calibration, i.e., the transfer functions for bias correction has been estimated for 29 years and then these transfer functions are applied to the remaining validation period (1 year). This procedure is repeated by leaving each year out in turn. Finally, all 30 one-year validated data has been grouped into a whole 30 years to evaluate with the 30 years observation data. The root mean square error (RMSE) is calculated based on 30 years mean daily precipitation rather than by averaging the error of each year since there is no relationship between every individual year of the RCM and observations. (i.e., RCM data in 1961 have nothing to do with observations in 1961). Only the statistical properties can be compared between RCM data and observations.

## 4. Results

### 4.1 Comparison between RCM data and Observations

To assess the performance of the 11-member RCM data for the baseline period, monthly mean precipitations for the Thorverton catchment have been compared between the RCM data and observation data. Figure 6 shows that the trend is similar but actual values do not match, and there are clearly biases between the observation and climate model during the baseline period. 11 RCMs tend to produce more rainfall than the observed between February and June, but less between August and December. Therefore, the biases exist in time (Figure 6 (left)) and in rainfall intensity (Figure 6 (right)).

### 4.2 Comparison of bias corrected data

Figure 7 shows 30 years mean observed precipitation and RCM precipitation after bias correction with daily data. We can see that the more groups we divide for bias correction, the less biased the corrected data is. This is because if bias correction period is shorter, temporal distribution of time series can be considered with more details than a bias correction period which is longer and as a result rainfall characteristics can be matched more sophisticatedly between the observation and the simulated data. However, on the contrary, the higher the number of groups, the higher the variance will be. This is a well-known trade-off between bias and variance in mathematical modelling (Figure 8).

The variance can be explained by the stability of transfer functions in the quantile mapping method. Each bias correction group has transfer function respectively as shown in Figure 9. One group with only one transfer function is too stable and 120 groups with 120 different transfer functions are too unstable with high variance. This is the same when the change of transfer function across time is considered. Transfer functions have two Gamma distribution parameters (shape and scale parameter) and as we can see in Figure 10 parameters in one group are constant across time which are too stable, while 120 group's parameters are too unstable across time. The more groups we divide, the more unstable the transfer functions become due to large variations.

### 4.3 Digital filtering results

To set the cut off-off frequency of the precipitation, spectral analysis of the observed flow has been done. Figure 11 presents the power spectrum of the observed flow and the observed precipitation data after the Fourier Transform. The amplitude of the flow spectrum decreases until the frequency is 0.05 and afterward it fluctuates. Hence, 0.05 has been set as the cut-off frequency for both the observation and RCM precipitation data.

Figure 12 presents the signal of the 30 year mean observed precipitation and the signal of bias corrected precipitation (3-day bias correction and 360-day bias correction) after removing the noise. We can see that the time series of 3-day bias corrected precipitation is much closer to that of the observed precipitation than 360-day bias correction. However, it does not mean that more groups are better than fewer groups as mentioned in section 4.2. When we compare the residual sums of squares (RSS) between unfiltered data and filtered data in Figure 13, it is clear that RSS of the original precipitation is much bigger than that of the filtered precipitation because the original data has high frequencies in the rainfall. Figure 13 shows the trend of RSS across different bias correction groups and the comparison between using filter and without using filter. RSS becomes smaller when the bias correction groups are divided in larger numbers for both filtered and unfiltered cases since if the correction period become shorter even the noise of natural variation will be matched closer to the observed data, although the magnitude and the slope of this decreasing trend is smaller when the noise is removed than using the unfiltered data. However, the trend of the value of $n \times ln(\mathrm{RSS}/n)$ in Equation (4) is quite different to that of the RSS value. The more bias correction groups are divided, the faster the slope goes down when only signal is considered than both the signal and the noise being considered, which means that the value of $n \times ln(\mathrm{RSS}/n)$ is very sensitive to the small RSS value. This is due to the feature of natural logarithm and this $n \times ln(\mathrm{RSS}/n)$ shape affects the shape of the AIC value which is referred in the next section.

### 4.4 Evaluation of the number of bias correction groups

To explore the optimal number of bias correction groups the AIC method is used and to evaluate the performance of different bias correction groups leave-one-out cross validation is applied. Figure 14 presents the AIC values for three different low pass filters and one AIC value without using the filter. The results show that the optimal number for bias correction groups in this catchment is about 8 days (the lowest AIC) for all three cases when only the signal is considered. If both signal and noise are taken into account the AIC value is almost similar from 30-day bias correction period to 360-day bias correction period which is not reasonable. This is due to high frequencies of rainfall data (i.e., noise) which make the RSS value very significant as mentioned in section 4.3 and in Figure 13. Figure 15 shows the RMSE of validated data for three different low pass filters and the results showed that the optimal bias correction period is about 8-day which is the same as the AIC result.

## 5. Discussion and Conclusions

The purpose of this study is to explore the optimal number of bias correction groups for climate model simulations. From the intuition, the more groups we have, the smaller temporal error will be in the bias correction. However, we may come to meet the overfitting issue and there is a question on the well-known trade-off between bias and variance. This is because smaller temporal error may not mean it is a good bias correction if bias correction fits to noise in the data instead of the underlying signal. Hence, we cannot judge by the temporal error alone. To resolve this issue and evaluate the performance of the models that have different numbers of bias correction groups the Akaike information criterion (AIC) and leave-one-out cross validation method are used for choosing the optimal number of bias correction groups. The results showed that for the case study catchment with the regional climate model, about 45 groups (8 days bias correction) has shown the lowest AIC and RMSE value i.e., the best setting for bias correction. We would like to reiterate that the proposed methodology uses only one grid of the Exe catchment which is located in the southwest of England, one emission scenario (A1B) and one-member (Q0) among 11-members of HadRM3 RCM precipitation because the purpose of this study is mainly to illustrate the logic of finding the optimal window size for bias correction of daily precipitation. This is the first time that such a problem has been addressed systematically. However, it should be pointed out that this study is only a preliminary attempt to address such an important but largely ignored issue. We hope it will stimulate more research activities to improve (or even falsify) the proposed methodology with different climatic conditions so that more experience and knowledge could be obtained.

Here are some possible problems to be explored further. Firstly, more studies are needed about the methodology to find the patterns of the optimal bias correction period at different parts of the world for different application purposes. In this study, AIC and leave-one-out cross validation are used to find the optimal bias correction period and it is possible that this optimal bias correction period is related to local climate and the purpose of the data usage. We do not think that this study has completely solved this problem. Maybe there are some alternative methods other than AIC or cross validation such as Bayesian information criterion

(BIC), but we have not found a way to verify them yet. Secondly, it is still uncertain that how strong the filter should be. This study has been done from rainfall point of view. Rainfall data time series is made of signals of different frequencies (high frequency, low frequency, and others…). Depending on what is the purpose for the data, we should use digital filters of appropriate frequency bands to remove the high frequency signals and only keep the useful signals relevant to the purpose of the data usage. In this study, low pass digital filter is used to filter out high frequencies because fluctuations make it difficult to find out how long periods are the best for bias correction. The cut-off frequency of precipitation has been chosen on the basis of the power spectrum of the observed flow since the catchment can be considered as a low pass filter. We intended to try different filters to find out if the results are sensitive to filter settings but the results seem quite consistent with different filters. Thirdly, compared with rainfall, from water resources point of view the river flow generated by rainfall is important (e.g., for reservoir operations). However, the digital filter only emulates a catchment effect, but it is not a fully functional hydrological model. Hence, instead of using a digital filter to remove the high frequency rainfall signal, we should use a catchment model as a 'low pass filter' to smooth out the high frequency rainfall signal. Similar to rainfall data, the results may be different if different water balance periods are interested by the hydrologists (hence hydrological models with different time intervals may be used). If we are interested in monthly water balance in water resources management, the high frequency flow signal should be further smoothed by a digital filter (on the flow data instead of rainfall). On the other hand, urban stormwater management is interested in rainfall in hours or even minutes. An appropriate filter frequency band for an urban catchment would be different. Fourthly, the impact of different window sizes to water resources management is an important issue. The ultimate test is to check whether different window sizes could have a major impact to the final decision. However, it is extremely complex to solve it. The answer will depend on a cascade of simulations and analyses including the rainfall-runoff modelling, water allocation modelling and the decision making process. In addition, it might be different for different catchments, different climate conditions with different water resources availability and utilisation. Therefore it is quite a complex problem to work out the impact of window sizes and at this stage we cannot answer this question. Because of the complexity on assessing hydrological impacts, most hydrological modelling studies have just focused on improving the model accuracy judged by a few selected criterions such as RMSE, $R^2$, etc. Few studies have been carried out to check if the improvements of the hydrological model have any real impact to the final decision making. Therefore, there are research gaps between the model accuracy and the real impact. Although we cannot illustrate the impact of different window sizes at this stage, it should pointed out that this study is a preliminary attempt to address the potentially important issue which has not been proposed before and suggested one possible methodology. We do not claim that our methodology is the only 'true' solution. The current practice is mainly 'rule of thumb' based on the 'gut feeling' of the researchers. A systematic method based on evidence is urgently needed. There are no doubts that this paper is likely to attract debate and discussion on this potentially important issue that has been largely unaddressed by the community. We hope it will stimulate more research activities to improve the proposed methodology (or to even falsify it) with different climatic and geophysical conditions so that more experience and knowledge could be obtained. It is possible that the real impacts of different bias correction window sizes could emerge after such an issue is addressed more widely by the community.

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